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MEASURING JOB AND PATIENT SATISFACTION IN PRESENCE OF MISSING VALUES: A CASE STUDY WITH INTERVAL IMPUTATION

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***Abstract**: The evaluation of Satisfaction within a given Organization has a twofold perspective: from the customer/user and the employee point of view. The presented case study is set up in the Ophthalmology Departments of the hospital "Spedali Civili" in Brescia and Montichiari. Job and Patient Satisfaction are investigated by means of two structured questionnaires and composite indexes are obtained with statistical procedures. The construction of a Satisfaction index has to face two main statistical problems, the former related to the ordinal scale of Satisfaction judgements, the latter caused by the frequent presence of missing values. In this paper Nonlinear Principal Component Analysis is applied together with a specific technique for missing values treatment, called Interval Imputation.*

***Keywords**: Satisfaction, nonlinear principal component analysis, missing values, symbolic data analysis, interval imputation.*

1. Introduction

The notion of Satisfaction has several domains. The most widely explored issue in this framework is perhaps *Customer Satisfaction* (CS), but many different applications analogously deal with *User Satisfaction* (US, in public services), *Patient Satisfaction* (PS, in medical services), *Job Satisfaction* (JS, from the employees' perspective).
On the whole, the analysis of Satisfaction has several interesting concerns both from an economic and a statistical point of view. For example, the economic literature puts the accent on the relationship between JS and CS/US/PS, emphasizing the fact that higher levels of JS could

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imply an improvement of the worker's performance and, consequently, of the quality of the supplied product/service.

On its hand, statistical theory focuses on the techniques for investigating and measuring Satisfaction. The analysis is carried out on the basis of the judgements acquired from the subjects (either the customer or the user/patient/worker), by means of a structured questionnaire. The main methods for acquiring Satisfaction judgements are:

- the use of a single question, asking for an overall opinion about Satisfaction (*Overall Satisfaction*);
- the arrangement of a set of items, asking for Satisfaction judgements about several different aspects of the product/service/job (*Facet Satisfaction*, FS).

With the second approach, specific statistical techniques are usually employed, in order to obtain a composite Satisfaction index, taking into account all the single FS judgements. These techniques can be quite simple (sometimes rather rough, like the average), or more sophisticated. In the construction of a composite Satisfaction index, two main problems have to be faced:

(i) the ordinal scale of FS judgements, typically obtained through Likert-type variables;
(ii) the possible presence of missing values, generally due to the incapacity or the unwillingness of the subjects, in certain cases, to formulate a judgement on a specific matter.

Among the several techniques developed in the context of the problem (i), we can recall

- the dimensionality reduction procedures, including the recent methods, like Nonlinear Principal Component Analysis ([6]), allowing to take into account the ordinal scale of FS judgements by means of optimal scaling procedures;
- the methodologies originally proposed in the psychometric field, and then adapted in this framework, like the Rasch model ([8]).
- the approaches considering Likert-type variables as the expression of numerical variables, like the PLS Path Modeling technique ([9]);

This paper presents a case study dealing with a survey set up in the Ophthalmology Departments of the hospital "Spedali Civili" in Brescia and Montichiari in order to investigate Job and Patient Satisfaction. The composite Satisfaction indexes are obtained by means of the method of Nonlinear Principal Component Analysis, adapted to operate in tandem with Interval Imputation, a specific procedure for missing values treatment ([10, 12, 13, 15]).

The paper is organized as follows: in Section 2 some background concepts about Principal Component Analysis (PCA) with interval data and Nonlinear Principal Component Analysis (NLPCA) are briefly recalled, in Section 3 the missing values treatment method called Interval Imputation is presented, the results of the survey are reported in Section 4 and Section 5 concludes.

2. Background concepts

It is well-known that PCA is aimed at reducing the dimensionality of a data set consisting of p quantitative variables $X_1, X_2, \ldots, X_p$, while retaining as much as possible of the variation present in the data set. PCA consists in a linear transformation to a new coordinate system such that the new set of variables $Y_1, Y_2, \ldots, Y_p$, the Principal Components (PCs), are uncorrelated, and the orthogonal projections of data on the one-dimensional spaces spanned by the PCs have

respectively the greatest variance, the second greatest variance, and so on. The dimensionality reduction is then achieved retaining only a *small* number q of PCs, possibly accounting for a *high* percentage of the total variation. From a geometrical point of view this corresponds to an orthogonal projection of data in the q-dimensional subspace spanned by the first q PCs.
In the last decades the basic idea of PCA has been developed in several directions. In this paper we are mainly interested to two issues: the possibility to perform PCA on categorical variables and on interval data. In this section two proposals in these contexts are briefly recalled (see paragraphs 2.1 and 2.2, respectively).

2.1 The basic concept of NonLinear PCA

NLPCA ([6]) is a technique which makes it possible to apply PCA to data sets composed (also) by categorical variables. It is based on the idea of simultaneously transforming categorical variables into quantitative ones and reducing the dimensionality of the data. In this way it functions as a nonlinear equivalent of traditional PCA. The transformation of categorical variables is made by means of an *optimal scaling* procedure aimed at assigning optimal quantifications to the original categories. Category quantifications are optimal in the sense that the variance accounted for by the PCs of the transformed variables is maximized. This maximum is conditioned to the number q of PC we want to retain, so the solutions, found by means of an Alternating Least Squares (ALS) algorithm, for different qs are said to be *non-nested*. This means that the first k PCs of a q_1-dimensional solution are different from the first k PCs of a q_2-dimensional solution ($k \leq q_1, q_2$ and $q_1 \neq q_2$).
In the optimal scaling process, we choose an optimal transformation function (or scaling level). The scaling level defines the way we take into account information in the original categorical data when computing the optimal quantifications. The least restrictive level is the *nominal* scaling level, a non-monotonic transformation which preserves, in the quantifications, only the grouping information given by the original categories. The *ordinal* and *spline ordinal* scaling levels are monotonic transformations preserving grouping and ordering information. Finally, the *numerical* scaling level is the most restrictive level and consists in a linear transformation preserving interval information beyond grouping and ordering. When numerical scaling levels are chosen for all variables, NLPCA turns out to be equivalent to traditional PCA.
NLPCA is useful when dealing with categorical variables, but also with numerical variables when they are supposed to be related by nonlinear relationships.

2.2 The idea behind the Vertices Method for PCA on interval data

Recently, a new concept of data analysis has been developed under the heading of Symbolic Data Analysis (SDA, initiated in 1987 by E. Diday, [4]). With SDA we are able to process data matrices where the generic element x_{ij} is not necessarily a single quantitative or categorical value, but can be, for example, a distribution as well as an interval, or a set of values linked by some logical rule. SDA includes techniques covering several fields of data analysis (see [1], for a review).
In this paper we are interested to the possibility to perform PCA on interval-type variables, that is on variables with interval valued measurements. The most popular technique in this context is the Vertices Method of Cazes et al. [3]. The basic observation of Vertices Method is that a subject, measured by means of p interval valued variables, can be considered a hyperrectangle in a p-dimensional space, instead of a point, as in the traditional data analysis methods. Since a p-dimensional hyperrectangle has 2^p vertices, for each subject it is possible to build a $2^p \times p$ matrix

containing the vertices of the hyperrectangle. PCA on interval valued measurements is then carried out by applying traditional PCA to the $N2^p$ x p data matrix obtained stacking below each other all the matrices containing the vertices of the hyperrectangles corresponding to each one of the N subjects. When the first q PCs have been selected for dimensionality reduction, the hyperrectangles' vertices are orthogonally projected into the subspace spanned by the PCs, thus each subject is represented in the q-dimensional space by a scattering of 2^p points, instead of by a single point as in traditional data analysis.

3. Interval Imputation

In order to perform PCA or NLPCA on a data table with missing values, two main options are possible: operating listwise or pairwise deletion or somehow imputing proper values to the missing. Alternatively, a recently proposed procedure called Interval Imputation (InI – [10, 12, 13, 15]), consisting neither in deletion nor exactly in imputation, can be used. According to InI, every missing value is replaced by a closed interval ranging from the minimum to the maximum value admissible for the concerned variable. When the range of the variable domain is not finite or it is unknown, we can opt for an interval containing the missing observation with a given probability, relying on some distributional assumption or on Chebyshev inequality ([15]). In the context of Satisfaction measurement ([12]), a missing value occurs when a subject is not able, or does not want, to formulate a judgement about a given FS item. If FS judgements are acquired by means of a Likert-type scale with k categories, ranging from "completely unsatisfied" (1) to "completely satisfied" (k), according to InI each missing datum is replaced by the exhaustive interval $[1,k]$.

Filling blanks with intervals produces a dataset composed by a mix of single-valued and interval-valued measurements, which can be processed using SDA.

The Vertices Method described in the previous section can be applied to the data matrix generated by InI, because the single-valued measurements can be considered as limiting cases of degenerate intervals. Due to the presence of single valued measurements, each subject in the InI matrix is a m_i-dimensional hyperrectangle defined in a p-dimensional space, where $m_i<p$ is the number of missing of ith subject. If $m_i=0$ the subject is represented by a point, if $m_i=1$ by a segment, if $m_i=2$ by a rectangle, if $m_i=3$ by a cube, and so on. Following the Vertices Method, for each subject a 2^{m_i} x p matrix can be built, containing the vertices of the hyperrectangle. Since each subject has to be given the same weight in the analysis, each 2^{m_i} x p matrix is replicated 2^{M-m_i} times, where $M=\max_i\{m_i\}$. A $N2^M$ x p matrix is then obtained stacking below each other all the matrices containing the (replicated) vertices of the hyperrectangles corresponding to each one of the N subjects. For further details about the construction of the vertices matrix, see [10, 13].

When data are projected in the two-dimensional subspace, as typically happens in most analyses with PCA, each subject is represented by the projections of his/her 2^{m_i} hyperrectangle vertices in the plane spanned by the first $q=2$ PCs. Subjects with missing values are represented by means of irregularly shaped two-dimensional scatterings, which can be graphically described by their convex hull. Subjects without missing values, on their hand, project into single points. Thus, the representation of data in the plane spanned by the first two PCs shows a mix of points (the subjects without missing values) and polygons (the subjects with missing values).

The InI method has at least four major advantages:

- subjects with missing values are maintained in the dataset, and the information they contain, even if partial, is in any case recovered;
- the procedure does not need to fill blanks with subjectively imputed single values;
- the particular final representation of subjects with missing values allows to appreciate their peculiar fuzzy condition. In addition, in case of $q = 2$, the larger the number of missing of a given subject, the larger the area of his/her polygon;
- for a given subject with missing values, the missing information differently affects the shape of his/her q-dimensional scattering. The shape of the scattering differs in accordance with the loadings of the variables where the missing is located. For example, in case of $q = 2$, when the missing information regards a variable with high loading on the first PC, but low loading on the second PC, the resulting polygon in the plane has a large base and a narrow height.

The way used by InI to represent subjects with missing values allows to inspect some features of missing responses. For example, it is possible to understand if subjects with missing data tend to cluster together, if some categories of subjects tend to be more affected by missing data, or if missing information affects a given PC more than the others. The importance to examine the features of missing responses has been underlined by many authors (see for example [7]).

The composite indexes measuring Satisfaction levels derive from one-dimensional representations of the subjects (for example projections onto the first PC). Subjects without missing values are described by a single value, while subjects with missing values are described by a set of values. If we need average Satisfaction levels within groups (e.g. males and females), the fuzzy condition of some subjects has to be taken into account. For example, the average index could be itself interval-valued, with its lower/upper limit computed averaging the lower/upper limits of the one-dimensional projections ([10]).

It has been shown ([13]) that, under certain assumptions, there is little difference between the PCs obtained with InI and with pairwise deletion. However the peculiar representation of subjects affected by missing values and the interval representation of composite indexes constitute an improvement of InI on pairwise deletion, which does not allow to compute object scores for subjects with missing data. In addition, the cumulative variance accounted for by the first q PCs is systematically lower with InI than with pairwise deletion, and the difference can be insightfully interpreted as the effect of missing information on the quality of the dimensionality reduction.

In this study NLPCA is applied to the vertices matrix in place of PCA, in order to take account of the ordinal scale of measurement of Likert-type variables. In [12] simulation studies are worked out in order to compare this strategy with different missing values treatment approaches in the context of NLPCA.

4. A case study dealing with Job and Patient Satisfaction measurement

The presented case study derives from a survey carried out in June 2008, in the hospital “Spedali Civili” in Brescia and Montichiari. Job and Patient Satisfaction were investigated by means of two structured questionnaires filled in by the workers and the patients, respectively, of the Ophthalmology Department. The aim of the survey was to measure two kinds of Satisfaction, internal and external (from the workers' and the patients' perspective), and to investigate the presence of a possible relation between them. The approach to the problem is explorative.

4.1 Job Satisfaction measurement

In order to acquire JS judgements, each doctor and nurse working in the Ophthalmology Department both in Brescia and Montichiari hospitals (42 and 26 subjects, respectively) in June 2008, was requested to fill in a questionnaire asking for Satisfaction with 13 aspects of job (Table 1), divided into three categories, Relational (R), Organizational (O) and Professional (P).

Table 1. JS items in the workers questionnaire

How satisfied are you with….	
Relational	R1. …your personal fulfilment?
	R2. …the recognition by co-workers of your work?
	R3. …the patients recognition of your work?
	R4. …the relations with your superiors?
	R5. …the relations with your co-workers?
	R6. …the relations with patients?
Organizational	O1. …the working hours schedule?
	O2. …the workplace environment?
	O3. …your decisional and operative independence?
	O4. …the services for workers (nursery-schools, canteen, …)?
Professional	P1. …your pay?
	P2. …your achieved and prospective career promotions?
	P3. …your vocational training and professional growth?

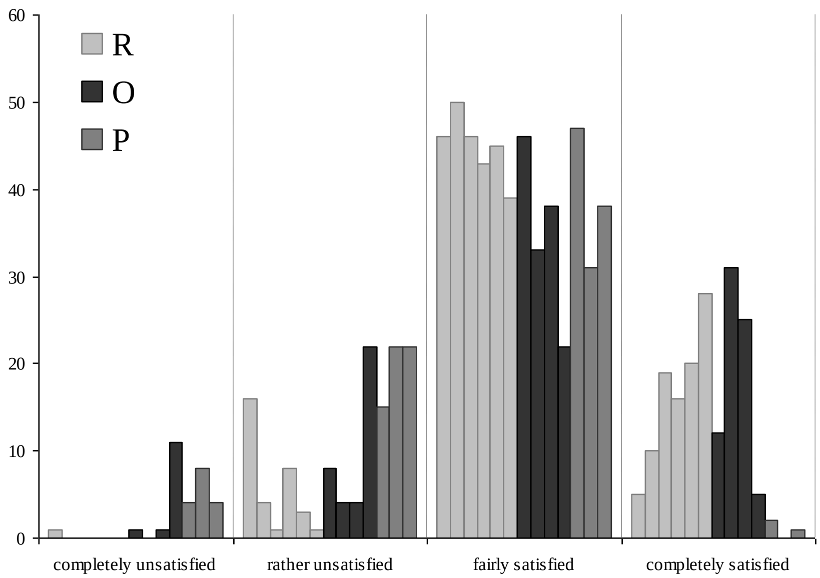

Figure 1. Frequency distributions of the answers to the single JS items, divided into the three categories, Relational (R), Organizational (O) and Professional (P).

The 68 respondents indicated their level of Satisfaction with respect to each aspect on a scale ranging from 1 to 4, with higher scores reflecting more Satisfaction. For the most part, the 68 subjects exhibited medium-high levels of satisfaction, as demonstrated by the frequency distributions of the answers to the single aspects (Figure 1).

On the whole, 9, 4 and 3 subjects were affected by 1, 2 and 3 missing values respectively, replaced by the interval [1,4]. The dimensionality reduction, operated by NLPCA with an ordinal scaling level for all the variables, shows the presence of two main factors, related to *Professional-Organizational Satisfaction* and *Relational Satisfaction* (Figure 2a), accounting for a 25% and 21% explained variance, respectively. This means that, as expected, relational aspects play a separate role in determining satisfaction with job, but the explained variance of the two components is almost the same.

(a) (b)

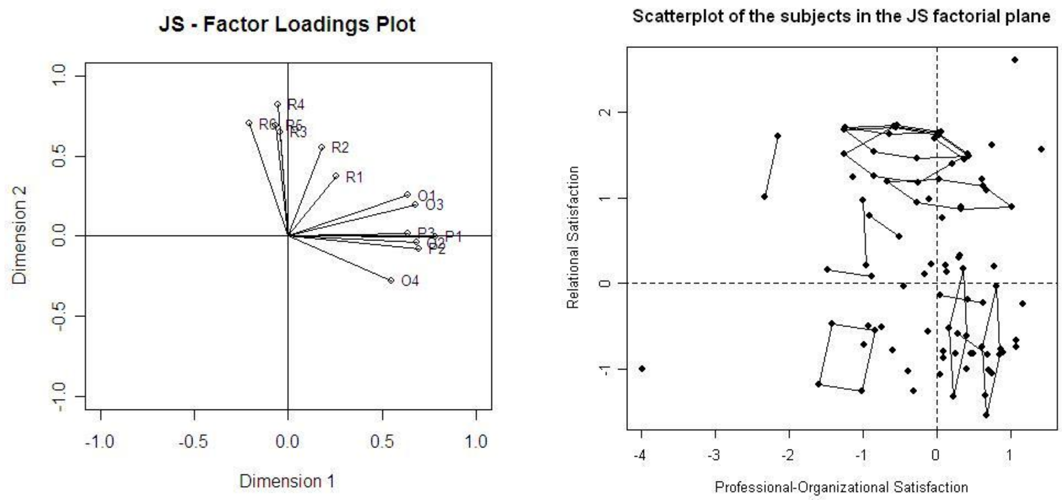

Figure 2. Factor Loadings Plot (a) and Object Scores Plot (b) for JS

Figure 2b displays the scatterplot of the subjects in the factorial plane. The subjects with missing values are represented by segments (1 missing) or polygons (2 or more missing). It is easy to see that subjects affected by 2 or more missing values have a very fuzzy location in the plane. Even so, they are rather well localized within quadrants, except for only one subject which largely overlaps 1^{st} and 2^{nd} quadrant.

Figure 3 shows the average Satisfaction levels in the two dimensions, separately for the two hospitals (Brescia and Montichiari), and for the kind of job (Doctor and Nurse). As pointed out before, due to the fuzzy condition of incomplete observations, interval-valued average Satisfaction levels are provided. Their lower/upper limits are computed averaging the lower/upper limits of the one-dimensional projections of each subject. In all the cases, the intervals do not overlap the *x*-axis. This means that, in spite of the missing information, the averages within groups are quite well localized with respect to the global average. The workers employed in the Montichiari hospital tend to be more satisfied both from the Professional-Organizational and the Relational point of view. From the point of view of the kind of job, doctors are more satisfied with the Professional-Organizational dimension, while nurses with the Relational one.

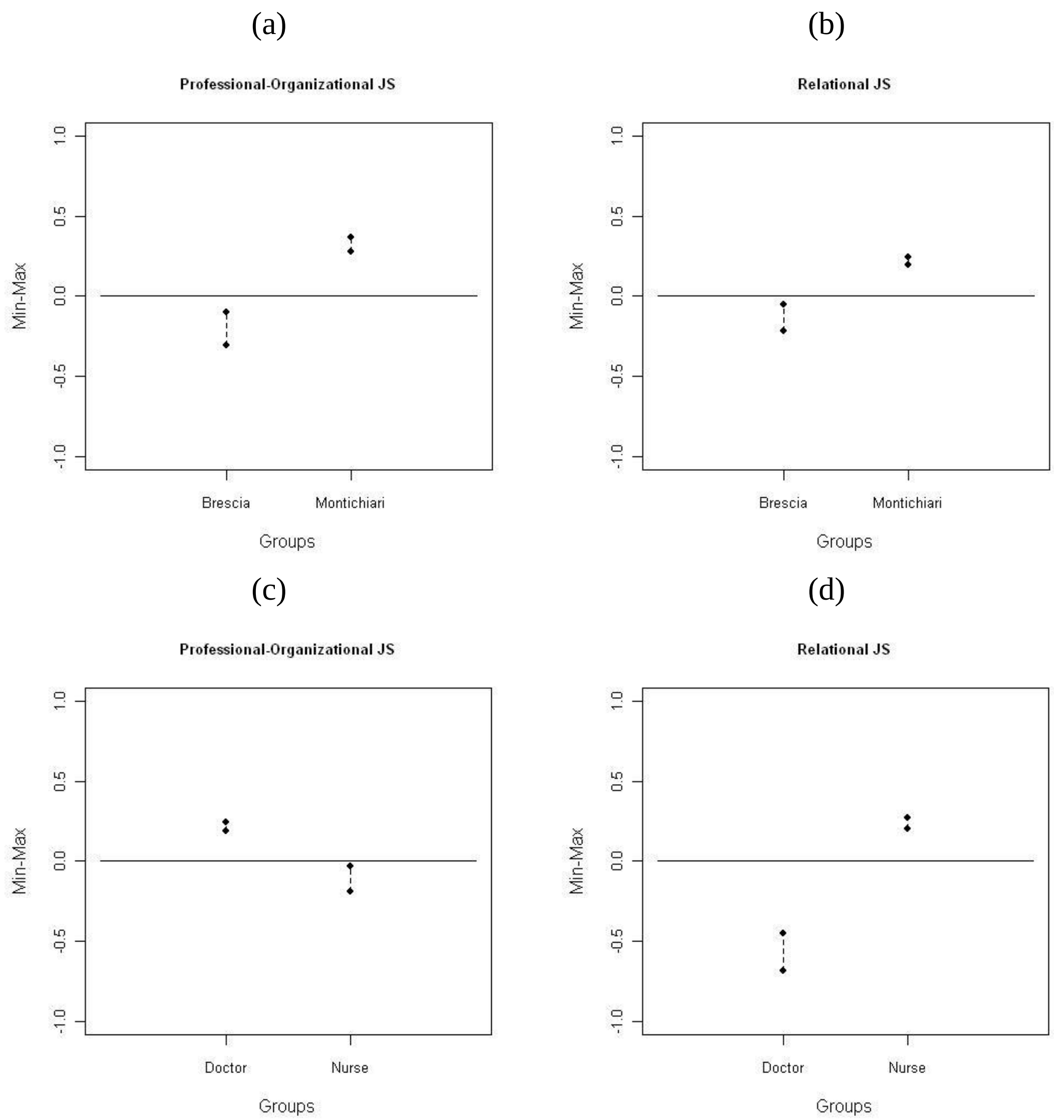

Figure 3. Average JS levels within groups for Brescia-Montichiari (a,b) and Doctor-Nurse (c,d)

A deeper analysis can be carried out taking into account the drivers of JS. Following [2] and [11], the overall JS[1] can be regressed on the FS judgements in order to investigate the role played by the different aspects of job in determining the overall JS. In this paper we use a nonlinear regression based on Treeboost ([5]), an algorithmic technique in the class of ensemble learning predictors, which starts fitting a decision tree to original data and then sequentially fits trees to current pseudo-residuals, computed according to some predetermined loss function. This scheme allows the construction of an interesting variable importance measure, called *relative influence* (see [5]), which gives an idea of the importance of the regressors (here the FS judgements) in predicting the outcome (here the overall JS). This permits to identify the drivers of JS, that is the

[1] A specific question about the overall JS was present in the questionnaire. The judgement was required in a scale ranging from 1 to 10.

aspects of job regarded by workers as the most valuable in determining their overall satisfaction with job (see [2] and [11] for case studies in a different context). Figure 4 displays the ranking of the FS items based on their relative influence on the overall JS.

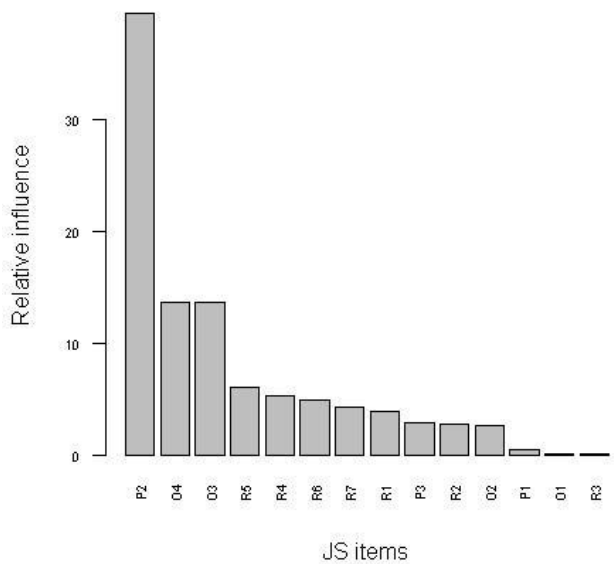

Figure 4. Drivers of JS, as revealed by relative influences on overall JS, computed with TreeBoost

It is immediately apparent that the most important driver of JS corresponds to achieved and prospective career promotions, which largely overcomes the other aspects.

4.2 Patient Satisfaction measurement

The PS analysis was carried on patients who underwent a cataract operation. The sample consisted of 81 patients, selected in Brescia and Montichiari hospital (49 and 32 patients respectively) in June 2008. Each of them was requested to fill in a questionnaire asking for Satisfaction with 16 aspects of service (Table 2), divided into three categories, Medical (M), Relational (R) and Organizational (O).

It is important to point out that in health care, quality is a controversial matter because its natural definition - the outcome in terms of health and quality of life gained by each patient - cannot be assessed since it depends on the specific characteristics of the patient.

In addition, the evaluation of medical quality requires knowledge beyond the ‘average patient’ and, for the single patient, the outcome (recovering health) may even be unrelated to the quality of care (appropriateness of the treatment used). For these reasons the items asking for satisfaction with medical aspects are intended to obtain information about the perceived quality of the delivered healthcare, which could be influenced by aspects other than strictly medical.

Similarly to the previous analysis, the scale ranged from 1 to 4, with higher scores reflecting more Satisfaction.

Table 2. PS items in the patients questionnaire

How satisfied are you with….	
Medical	M1. …the accuracy of your pre-operational visit?
	M2. …the way you were informed by the doctor about your condition?
	M3. …the accuracy of the cataract operation?
	M4. …the comprehensibility and completeness of information about your problem?
	M5. …the comprehensibility of your recommended post-operational behaviour?
	M6. …the quality of the healthcare delivered by the doctors?
Relational	R1. …the humanity and the helpfulness of the doctors?
	R2. …the politeness and the efficiency of the nurses?
	R3. …the attention to your privacy?
	R4. …the quality of the relationships in general?
Organizational	O1. …the appointment scheduling service?
	O2. …the waiting time for an appointment?
	O3. …the hygienic condition and the disinfection of the environment?
	O4. …the technologic level of equipments?
	O5. ...the punctuality?
	O6. …the general organization?

On the whole, the frequency distributions of the answers of the 81 patients to the single aspects exhibit high levels of satisfaction (Figure 5).

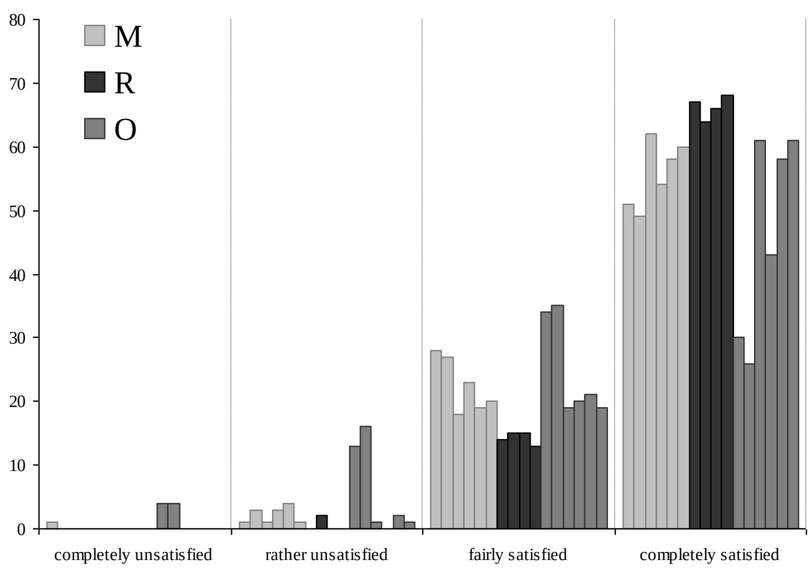

Figure 5. Frequency distributions of the answers to the single PS items, divided into three categories, Medical (M), Relational (R) and Organizational (O).

In this case, 18 and 1 subjects were affected by 1 and 3 missing values respectively, replaced by the interval [1,4]. The dimensionality reduction operated by NLPCA shows the presence of two main factors, related to *Medical-Relational Satisfaction* and *Organizational Satisfaction* (Figure 6a), accounting for a 42% and 17% explained variance, respectively.

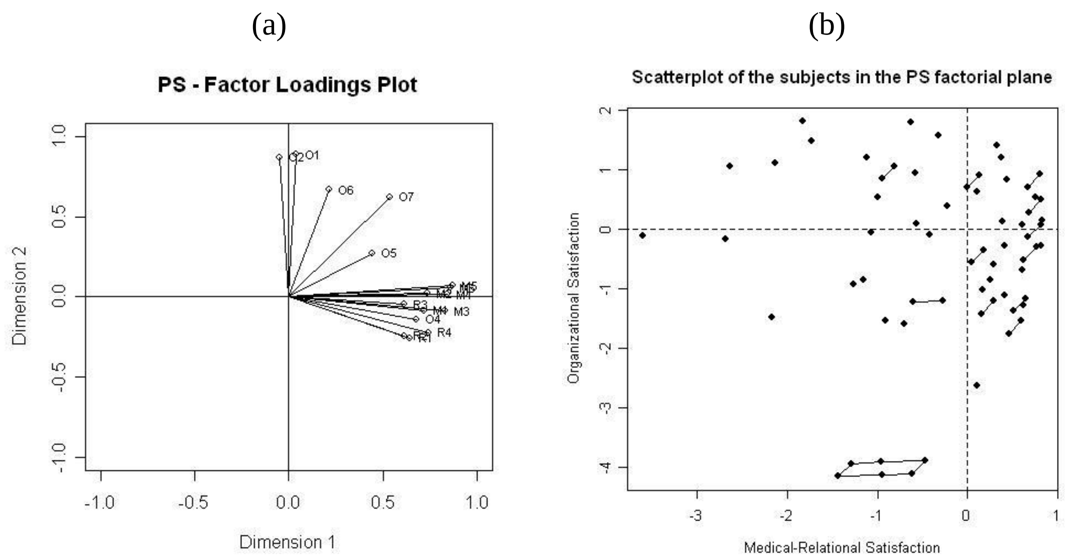

Figure 6. Factor Loadings Plot (a) and Object Scores Plot (b) for PS

This mainly means that:

- The perceived quality of the delivered healthcare is connected to relational aspects and not to organizational quality. In other words, patients tend to join medical and human care into a unique attribute of healthcare, uncorrelated to managerial efficiency.
- The variance explained by the perceived quality of the delivered healthcare is more than double with respect to organizational quality, meaning that it accounts for a great part of the PS variability.

Figure 6b displays the scatterplot of the subjects in the factorial plane. It shows that the missing information scarcely affects the positioning of subjects in the factorial plane. Only one subject is represented by a moderately large polygon, but its fuzzy location is completely contained in a zone revealing low Satisfaction on both dimensions without uncertainty.

Figures 7 show the interval-valued average Satisfaction levels in the two dimensions, separately for the two hospitals (Brescia and Montichiari), and for the person who filled in the questionnaire (the patient himself or a relative). The patients of Brescia tend to be more satisfied with the Medical-Relational dimension, while those of Montichiari are more satisfied with the Organizational one. On the other hand, when the questionnaire is filled in by a relative of the patient (this happened in case of very old patients), the average Medical-Relational Satisfaction is appreciably higher than when the respondent is the patient himself (does it mean that we are more easily satisfied when it is someone else who underwent the operation….?). In the Organizational dimension, there is no noteworthy difference from this point of view.

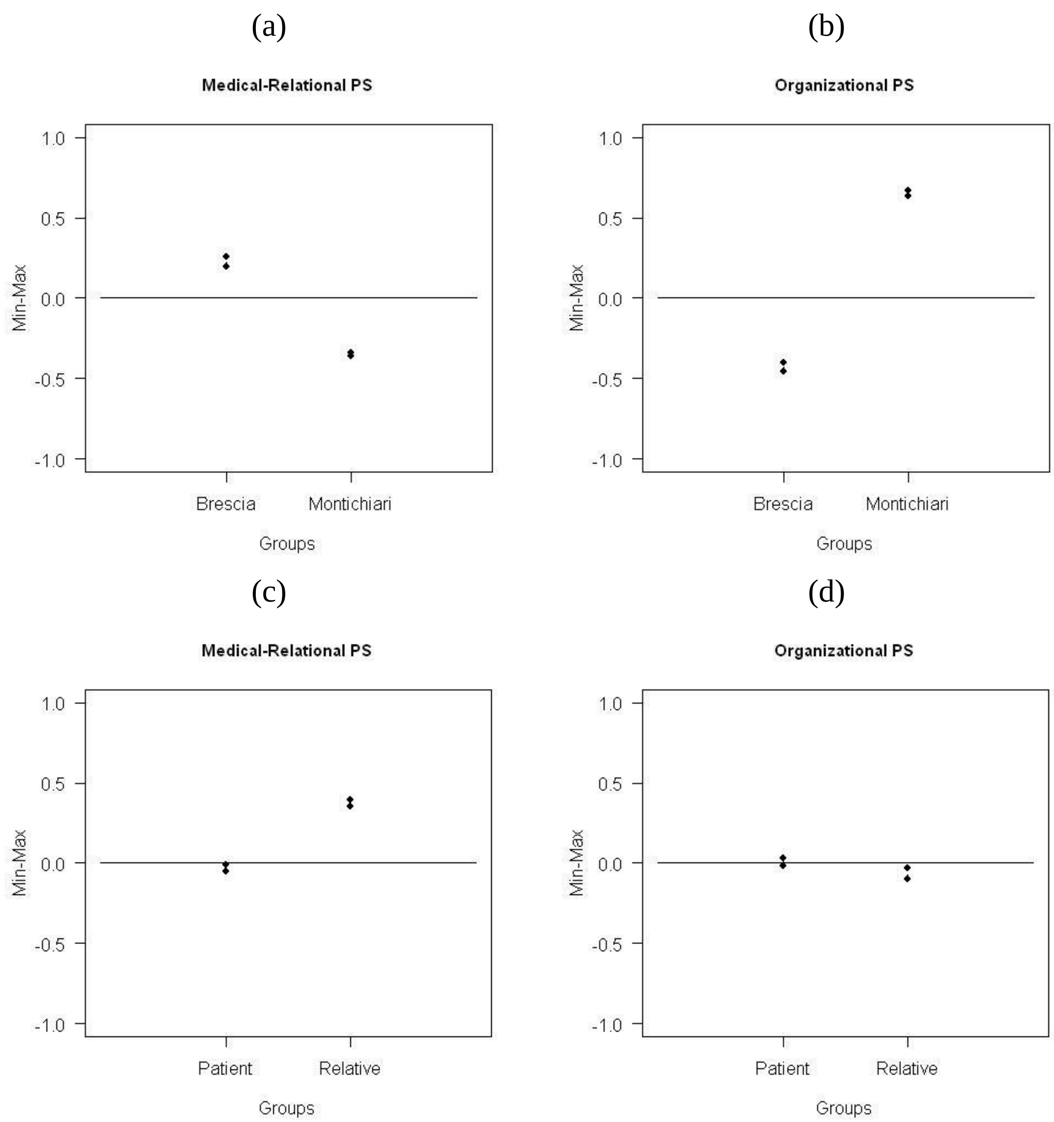

Figure 7. Average PS levels within groups for Brescia-Montichiari (a,b) and Patient-Relative (c,d)

As for the JS analysis, also in this case it is possible to obtain the drivers of PS by means of the relative influences computed with TreeBoost (Figure 8).

As expected, the most important aspects of PS are medical, but it is interesting to notice that they are related to information instead of the accuracy of the operation. As recalled before, patients are not able to evaluate the quality of the healthcare and the appropriateness of the received treatments. For this reason they formulate an overall judgement relying on secondary aspects like the way they are informed about their health problems. A learned doctor who gives scarce consideration to the patient and does not adequately inform him, risks being considered untrustworthy.

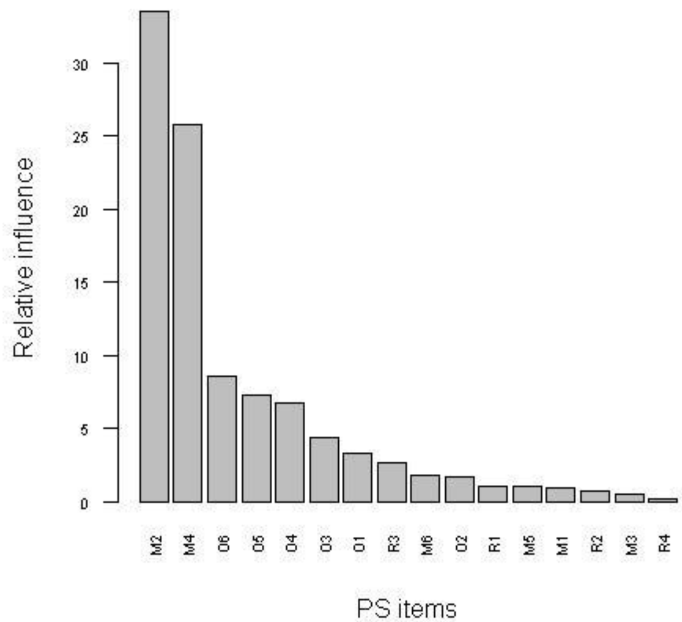

Figure 8. Drivers of PS, as revealed by relative influences on overall JS, computed with TreeBoost

4.3 Job versus Patient Satisfaction

The analysis presented in section 4.1 brings to light that JS is higher in Montichiari than in Brescia both in the Professional-Organizational and in the Relational dimension. The question naturally arising now is if this has any consequences on the perceived quality of the delivered service. In other words, we ask ourselves if higher levels of JS produce higher levels of PS. In the left part of Figure 9 the interval-valued average indexes of Professional-Organizational JS are plotted against the interval-valued average indexes of Organizational PS, separately for Brescia and Montichiari. Similarly, the right part of Figure 9 shows the interval-valued average indexes of Relational JS against the interval-valued average indexes of Medical-Relational PS.

(a) (b)

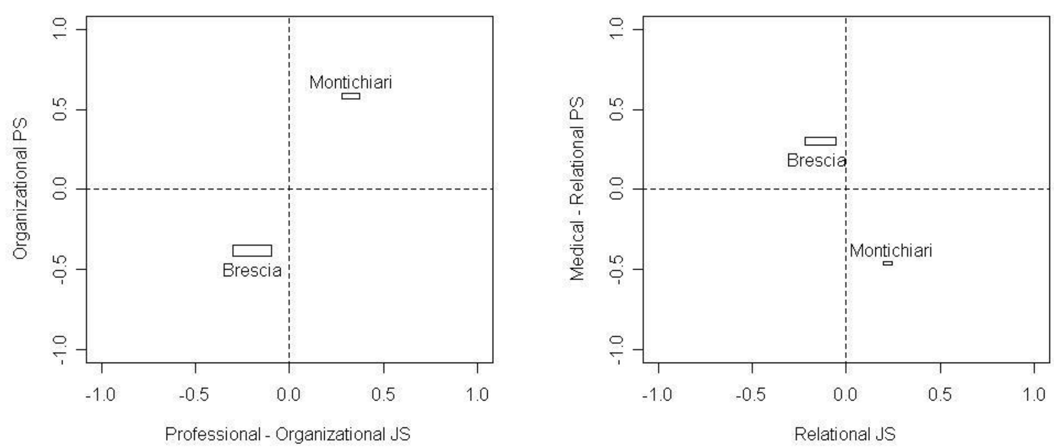

Figure 9. JS versus PS in the two hospitals

The organizational superiority of Montichiari is confirmed both from the workers and the patients perspective. Of course much of this depends on the fact that Montichiari is a small decentred hospital with the organizational facilities of a little structure. Thus, from this point of view the source of high satisfaction (both JS and PS) has almost certainly to be searched in this “external” factor.
More interestingly, the lower level of Relational JS in Brescia does not correspond to a lower level of Medical-Relational PS. In order to interpret this evidence, we must consider that on the whole PS is very high (Figure 5) and completely unsatisfied patients, expecially in the Medical Relational dimension, are nearly absent both in Brescia and in Montichiari. Hence we are dealing with little differences in PS, which could be not significant.
Another point is that workers in a great hospital like that of Brescia could be more organized and demanding, hence less disposed to declare high levels of JS. Anyway this does not influence the quality of their work, as revealed by the high levels of PS.
A last interesting observation about the joint analysis of JS and PS refers to the compliance of patients and workers with the survey and the questionnaire. The representation of subjects in the factorial plane according to the InI methods (Figures 2b and 6b) allows to easily observe that unwillingness and inability to respond occur mainly with workers.
In general patients are pleased to have their opinion taken into consideration. Quite the opposite, the workers can regard the survey as an intrusion in their work and hence could be more reluctant than patients to answer some questions. In Figure 2b we see that there are both horizontally-shaped and vertically-shaped polygons. This means that the reluctance or inability of workers in responding regards both the Professional-Organizational and the Relational aspects. From the point of view of patients, the missing values occur mainly with item O4 (about the technologic level of equipments) and hence we can suppose they are due to incapacity, and not unwillingness, to respond.

5. Concluding remarks

In this paper a structured case study concerned with satisfaction measurement is presented, based on a survey carried out in the Ophthalmology Departments of two hospitals. The aim of the survey was to measure Job and Patient Satisfaction, and possibly to compare them.
From a methodological point of view, two recent statistical techniques have been applied, Interval Imputation and Nonlinear Principal Component Analysis, for the treatment of missing values and the computation of composite satisfaction indexes, respectively.
The main results of the analysis are as follows. From the JS point of view, Relational aspects of job constitute a separate dimension, distinct from the Organizational-Professional sphere. The hospital of Montichiari, a small decentred structure, overcomes Brescia both in the first and in the second dimension.
In the patient perspective, things are quite different: the Relational domain is very strictly related to the Medical one, while the Organizational dimension plays a separate role. This evidence is commonly observed in PS studies (see for example, [14]): patients, both for their inability in evaluating the appropriateness of the treatments they receive and for their particular state of mind in a moment of disease, tend to consider the quality of relationships as a sign of the quality of the healthcare.

The comparison of JS and PS confirms the superiority of Montichiari from the organizational point of view, while no evidence is found about a relation between Relational JS and Medical-Relational PS.

Acknowledgements

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